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An Enhanced DMAIC Method for Feature-Driven Continuous Quality Improvement for Multi-Stage Machining Processes in One-of-a-Kind and Small-Batch Production

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ABSTRACT This paper proposes an enhanced DMAIC (eDMAIC) method which succeeds from Six Sigma tool for the machining processes in multi-stage, small-batch or one-of-a-kind (M/S/O) production. As a modification and extension of the popular Six Sigma DMAIC, the eDMAIC method also consists of five phases, i.e., define, measure, analyze, improve, and control. Several specific tools in each phase are offered and how to use them is also interpreted. Then, a continuous quality improvement case is illustrated on how the eDMAIC method carries out in a machining workshop. It is proved that eDMAIC method contributes to a systematic solution when the machining processes are unstable. The eDMAIC method also offers an engineering approach to realizing better quality performances with lower cost in the context of M/S/O production with Six Sigma thinking.

INDEX TERMS Lean production, quality management, machining, process control, performance evaluation, multi-stage, small batch, one-of-a-kind.

I. INTRODUCTION

Workpieces are evolving from mass production into *Multi-stage/Small-batch/One-of-a-kind* (M/S/O) one. And the *Machining Workshop* (MW) are also constantly transforming to serve these new production modes. Features of *Works in process* (WIPs) seem also very different than that in the traditional production, which is hard to control their machining processes because of the uncertainty in each process.

Meanwhile, transition of the production mode will always come with the methods of quality or process control, that the WIPs in M/S/O always have individualized quality and delivery time requirements. Traditional *Statistical Process Control*(SPC) and *Process Capability Index* (C_{pk}) are all mainly for the mass-production mode, which are not suitable in MWs for individualized products. Summarily, some weak of engineering, such as for*Quality Control* (QC) methods, data-integrating and continuous processes-improving, are in this kind of MWs, which can be detailed as follows.

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1) WITHOUT EFFECTIVE METHOD FOR CONTROLLING MACHINING QUALITY IN M/S/O PRODUCTION

SPC tools based on normal distribution are widely used in monitoring the process variation and identifying the variation sources. But in the M/S/O production, various data is heterogeneous, which means it is hard to detect the hidden tendency with limited data from different places in different processes. And there are also no tools for M/S/O production mode because traditional approaches, which work in the developed conditions where all the adjustments are hysteresis, have limitations. When a machining process is in the individual or developing state, the machining conditions cannot be controlled timely, which means the optional controlling methods will not take effect until the machining process is over.

2) WITHOUT TECHNOLOGICAL APPROACHES TO INTEGRATING AND USING THE RAW MACHINING DATA SYSTEMATICALLY

Data is the real reaction of the machining processes. Discovering the inherent relationships and the mutual influence rules among machining processes data are helpful to understanding the machining process deeper. The SPC tools and C_{pk} approach are all data-driven and they all play an important role in the traditional workshops. In the M/S/O production mode, the data are from different time, processes, places, and WIPs. They have features of large amount, highly discrete, low coupling, and low-value density. Integrating and making full use of these data systematically is vital to improving the performance of M/S/O machining processes. Besides, adjustments must be done while the batch size of order is extremely small. It is also necessary to collect data effectively and analyse them real-timely instead of concerning on the final quality performance.

3) WITHOUT CONTINUOUS TOOLS FOR EVALUATING AND IMPROVING THE MACHINING PROCESSES

In continuous process improvement efforts, the C_{pk} approach is a statistical measure of process capability: the ability of a process to produce output within specification limits. It is known that the mass-production is repetitive machining processes and C_{pk} represents the capability while machining the previous WIPs, which machining process has already finished. Similarity to the SPC tools, C_{pk} is also limited by the batch size of M/S/O production, which is the discrete machining process. DMAIC (an acronym for Define, Measure, Analyse, Improve and Control) method in Six Sigma field provides a reference for the continuous improvement of these discrete machining processes. DMAIC refers to a data-driven improvement cycle used for improving, optimizing and stabilizing processes. The DMAIC improvement cycle is the core tool used to drive Six Sigma projects. Also, it is needed to invent an enhanced index representing stability for evaluating and improving the machining processes continuously and systematically.

After a brief review of the engineering problems, a method for quality controlling and process improving in MW of M/S/O products is urgently needed. On the one hand, it can make progresses on the theory of QC and progress continuous improvement in guiding the machining in M/S/O production. And on the other hand, it is a supplement of production organization for better quality and more efficient process. In addition, WIPs in M/S/O productions are not all in MWs but they are the most complex and representative ones. So, this paper will focus on the machining process of WIPs in M/S/O production. The rest of this article is organized as follows. Section 2 is the literature review about quality controlling and process improving in the MWs. And an enhanced DMAIC (eDMAIC), as a modification and extension of the popular Six Sigma, is put forward in Section 3. Then, the next section 4 is the implementation of eDMAIC. In section 5, a case is studied to demonstrate the proposed eDMAIC method. Finally, ''Conclusion'' section describes the contributions and outlook of future work.

This proposed eDMAIC method is a novel approach for quality controlling and continuous process improving in MW. Based on the traditional DMAIC tool, eDMAIC tool is designed for the better-quality performance of M/S/O WIPs drawing on Six Sigma's thinking. It can fill the gaps in the standardization of machining processes' controlling in M/S/O production, which makes the Six Sigma Management suitable for more scenes.

This paper is intended to be a guide for the quality practitioner, who works via a continuous improvement tool when the statistical tool cannot be used. It is believed that this method can support the decisions whatever in the QC or the process management.

II. LITERATURE REVIEWS

M/S/O machining process is mainly present in the cloud manufacturing [1], distributed manufacturing [2], agile manufacturing and social manufacturing [3], [4]. Some researchers have been focusing on the machining process of WIP, especially on the QC and process capability evaluation. Some definitions, configurations, machining networks and key points & applications about WIP in M/S/O have been discussed. There are some researchers concerned about the QC issues in this M/S/O production mode [5], but the studies remain in the conceptual or the primary application phases [6], [7]. In addition, some intelligent algorithms such as artificial neural network (ANN) model has been used in the non-linear multiple-input multiple-output model of machining processes [8].

QC for WIPs in M/S/O production has the characteristics of distributed and decentralized, and there are two approaches to solving this QC problem. The FIRST one is based on statistical models. Enhanced SPC methods were applied to monitor and control the quality performance since Shewhart invented the Control Charts [9]. They all employed statistical models with measurable quality data so they were suitable for mass or medium batch production [10]. Control Charts are also popular ways in some small-batch production area [11], and fuzzy SVN tool was combined into the exception patterns recognition [12]. Some short run SPC techniques are passed from the research literature to practical use for many years, but these algorithms are mostly statistical-based and it is assumed that the machining processes are with the same or similar tool. The ANOTHER method is analysis-based, where a state space description model and an error propagation model were built for expressing the relationships between machining process and the machining error [13]. Then the influence of cutters, fixtures, and machines has also been studied with variation propagation modelling [14]. Complex system theory and complex network also play an important role in the M/S/O machining process, which can be seen as a systematic way in modelling the whole processes considering various variables digitally in MWs [15]–[17]. This method had made a progress with high technical bottleneck, which a firm or a workshop cannot carry out immediately. In addition, the analysis-based methods are non-real-time, which means the machining processes might be disconnected while calculating, and the cost of time will increase [18].

Process evaluation and continuous improvement for WIPs in M/S/O has also the characteristics of calculation-difficultly because of the data lacking [19]. Evaluations always contain two main aspects, which is capability evaluation (C_{pk}) and stability evaluation. C_{pk} is a statistic-based tool for measure capability, that it is meaningless to use its original definition for the M/S/O machining process. So many researchers have devoted to inventing an improved model for the small-batch processing evaluation, such as Bayesian approach [20], robust design [21], [22] and Quality & Reliability Chain [23]. Also, a six-bootstrap method was addressed to construct upper confidence bounds of incapability index C_{pp} for short-run machining processes [24]. Another evaluation is analysis approach, which is like the QC for WIPs in M/S/O production. The existing measurements of the robustness, stability, and performance of a process or a WIP might be classified into index-based approaches, experimental-based approaches, and sensitivity-based approaches [25]. Besides, a procedure was addressed for short-run production using the technique of principal component analysis [26]. Sensitivity analysis-based methodologies have been already used in measuring the robustness of a process or a WIP [27]. Also, a novel robust design technique is proposed based on the performance sensitivity distribution of a mechanism [28]. Nevertheless, these methods or tools go for the independent stage, and there is no tool to connect them in series.

DMAIC method is a very useful tool of Six Sigma in the process continuous improvement context [29]. It is usually used for improving the capability in mass-production mode including five phases - Define, Measure, Analyse, Improve and Control, each of which has its standard procedure [30], [31]. A lot of cases have been studied with DMAIC framework [32]–[36] and results show that the implementation of DMAIC method led to a significant financial impact on the profitability of the workshop. And some researchers have been focusing on the DMAIC in CNC machining processes [37] using the analytical hierarchy process and the entropy method [38]. Meanwhile, the tools which used for each phase are also sorted out and even the ISO 13053-1-2011 has already described a specific method application process [39]. It also recommends how Six Sigma projects should be managed, and describes the roles, expertise, and training of the personnel involved in such projects. In MWs, the M/S/O machining processes also have generalized Six Sigma quality requirements, which is the zero-defect (Six Sigma thinking) other than the 3.4 PPM. But there are many differences in the continuous process improvement between M/S/O production and mass-production.

To solve the problems in Section "Introduction," some research trends can be summarized based on the analysis of literature:

a) Statistical approach is not fit for M/S/O machining process, but the analysis approach, represented by the error propagation analysis, provides a possible way;
b) C_{pk} as a capability index has its own agreement definition, and how to figure out the value in M/S/O machining process has not yet defined. Thus, the stability index seems to be a more suitable evaluating;
c) There are many continuous process improvement methods proposed in the literature, including DMAIC, PDCA and so on. Nevertheless, finding a suitable method for M/S/O production is difficult.

To conclude, previous researchers have focused on the mass production with statistical tools, which needs enough samples. A novel method is badly needed for a more practical machining process evaluation and continuous improvement of M/S/O production in MWs. With using that, the quality and the machining process of M/S/O production might be under better control.

TABLE 1. Five stages overview of the eDMAIC project.

Stages	Overviews
Define	Define the object of the eDMAIC project. It might be a specific machining process in a MW. Define the goals of this eDMAIC activity. The most important goals are obtained from individualized needs. Define the eDMAIC team. The proper members are from the different departments of MWs. Define the timelines of this eDMAIC project.
Measure	Measure the existing machining processes with digital and mathematical tools. Model valid and reliable metrics for monitoring machining progress towards the object(s), goal(s), team(s) and timeline(s) defined in the previous process.
Analyse	Analyse the key processes which affect the final quality or efficiency restrictions along the machining line. Establish a valid and reliable Error Propagation Network (EPN) to help monitor machining towards the goal(s) defined at the first stage. Monitor the machining process. To get accurate calculations and analyses of eDMAIC project, the key machining process should be monitored.
Improve	Improve the stability of the key machining process that found at the previous stage. Use tools/methods to guide the forecast of final quality with pre-set metrics. When the defined stability index is less than the minimum threshold, some controlling approaches will be done in next stage.
Control	Control the machining process. Be creative in finding new ways to adjust the parameters which the machining system's inputs. Use planning and management tools for implementing these new approaches. Use numerical simulation and orthogonal experiment design methods to validate the improvement. Control the machining system. Institutionalize the improved system by modifying machining processes, procedures, and operating instructions. Utilize standardization such as ISO 9000 to assure that documentation is correct.

III. METHOD OF QC & CONTINUOUS PROCESS IMPROVEMENT - EDMAIC

Based on the analysis of the status quo of M/S/O machining process, an enhanced DMAIC method, that serves for QC and processes continuous improvement, is invented. Table 1 gives the functions of each phase of an eDMAIC

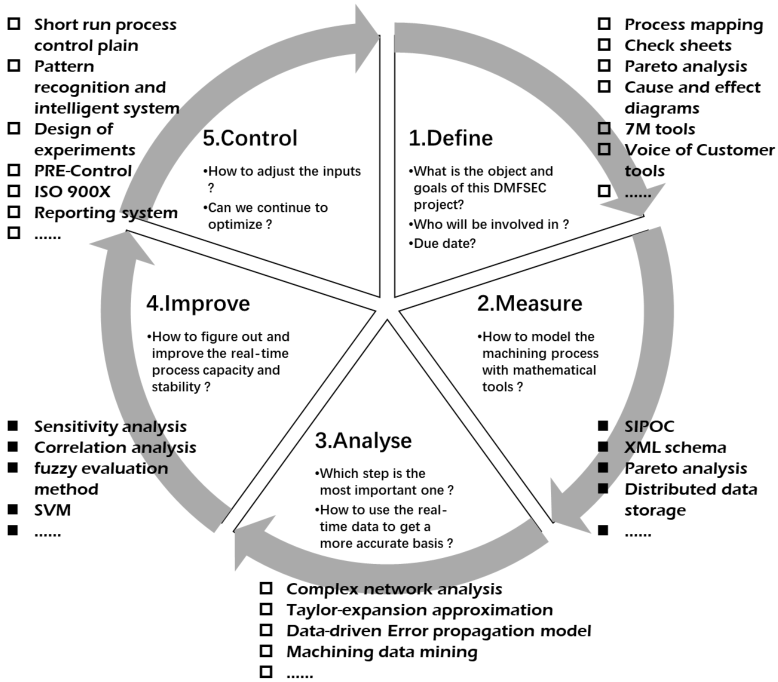


FIGURE 1. The eDMAIC cycle.

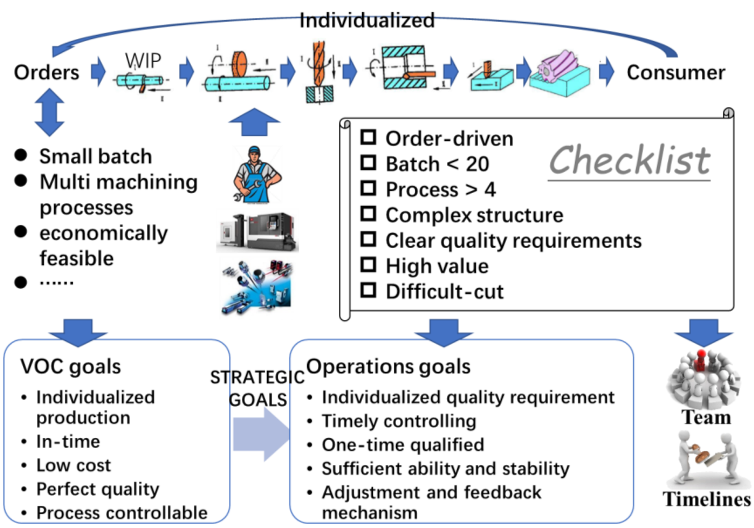


FIGURE 2. Define an eDMAIC project.

project, and the typical individual tools prescribed for delivering these functions. Noted that the eDMAIC and DMAIC have the same stages, but their contents are different.

eDMAIC provides a useful framework for conducting QC for M/S/O machining processes. It is a closed-loop controlling system, in which criteria for completing a phase are defined and projects reviewed to determine if all the criteria have been met, seen as Figure 1. And the list of available tools often found to be useful in each phase also shown in this figure. There is considerable overlap in practice.

IV. IMPLEMENTATION OF EDMAIC

The framework of the eDMAIC is described in Section III, while this section will describe the five corresponding phases' implementation, seen as below.

A. DEFINE

The **Define** phase ensures that the eDMAIC project selected is an M/S/O machining quality control and continuous machining process improvement problem, and it starts with identifying a machining issue that requires a controlling solution and ends with a clear understanding of the scope of this problem and evidence of management support [40]. Figure 2 shows the whole define items of an eDMAIC project.

1) OBJECT
The eDMAIC object is the MW, which might be a workshop aiming to produce M/S/O WIPs for the customized and individualized market [41]. It is noted that the MW is an unnecessary and sufficient condition for carrying out an eDMAIC project, which means the scope of eDMAIC is determined by the M/S/O characteristics. Whether a machining process can be selected for an eDMAIC project is followed by the checklist shown in Figure 2. Additionally, WIP of M/S/O in traditional factories might also meet the requirements.

2) GOALS
The goals of eDMAIC projects consist of three levels from *Voice of Customer* (VOC) to specific controlling objectives, details as follows.

a) Top goal goes to be the VOCs because the vital of an eDMAIC project is aiming to solve the QC or continuous machining process improvement issue which customers concern.
b) Project goals will be the strategic objectives, such as total quality performance or timely delivery, which will be more specific. (e.g., decrease the rejection rate, increase production capacity and one-time pass rate, without delay)
c) Operations goal goes to control the machining quality after key process or maintain the stability of the specified process.

3) TEAM
After defining objects and goals, an eDMAIC project team will also be selected. In general, eDMAIC project team consists of the customer(s) who has individualized machining and quality requirements, the crowding designer(s) who meets the need(s) and prepares the machining process, the manufacturer(s) who conducts the machining procedures, the quality assurance(s) who ensures the process and final qualities, and a leader who can take responsibility to the entire eDMAIC project. Team members should represent different levels of the organization to bring different perspectives to the eDMAIC goals. Then some mechanisms also are declared, such as the communicational plans and member's join & exit. Noted that the eDMAIC project team is a temporary organization and it will be disbanded once the project is over.

4) TIMELINES
Timeline guides QC & continuous machining process improvement plan of the WIPs and determines whether the delivery is on time. It should be adjusted once the machining quality fluctuating drastically, which indicates that the current stability is very poor.

B. MEASURE
The purpose of the **Measure** phase is to describe and model the whole information about the defined eDMAIC project with digital tools. There are two main items in this phase, details as follows.

1) GET ENTIRE IPOS OF EDMAIC
An *Inputs-Process-Outputs* (IPO) is a high-level mapping of the machining process being considered for eDMAIC method. IPOs stand for a generalized definition representing the assumed as-is process. IPOs can be developed concurrently with the eDMAIC project, and its drawing is shown in Figure 3.

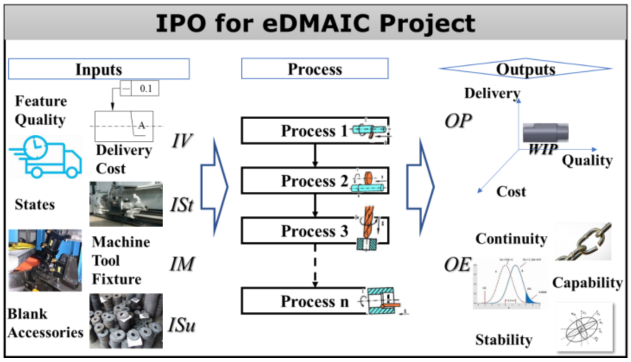


FIGURE 3. The IPOs for an eDMAIC project.

These globe IPO indexes are of the system-level, and there are IPOs in each process as well. All of these can form a machining route along processes. Then group all the inputs into the following categories in each process.

a) VOC (*IV*) indicates the most important one among all the inputs, which can support structure feature, quality, delivery time or cost.
b) State (*ISt*) stands for different conditions such as vibration, noise and so on, which can affect the outputs while machining.
c) Machining (*IM*), including machines, tools, and fixtures, are the factors that may influence the machining.
d) Supply Elements. (*ISu*) Supplies may have some defects that can lead to the unstable state of machining which needs to be taken into consideration in this phase.

The outputs contain these two categories similarly:

a) Product (*OP*), such as feature, quality, delivery time, and machining cost of WIPs, reply to the VOCs and their performances decide the achieve results of the eDMAIC project.
b) Evaluation (*OE*) indicates the performance of a machining process, and the stability index might be figured out.

Finally, repeat the above processes until all of them have inputs identified, then describe them digitally.

2) DIGITIZED DESCRIPTION
To facilitate the eDMAIC project better, each IPO in each machining process should be formally described, which is

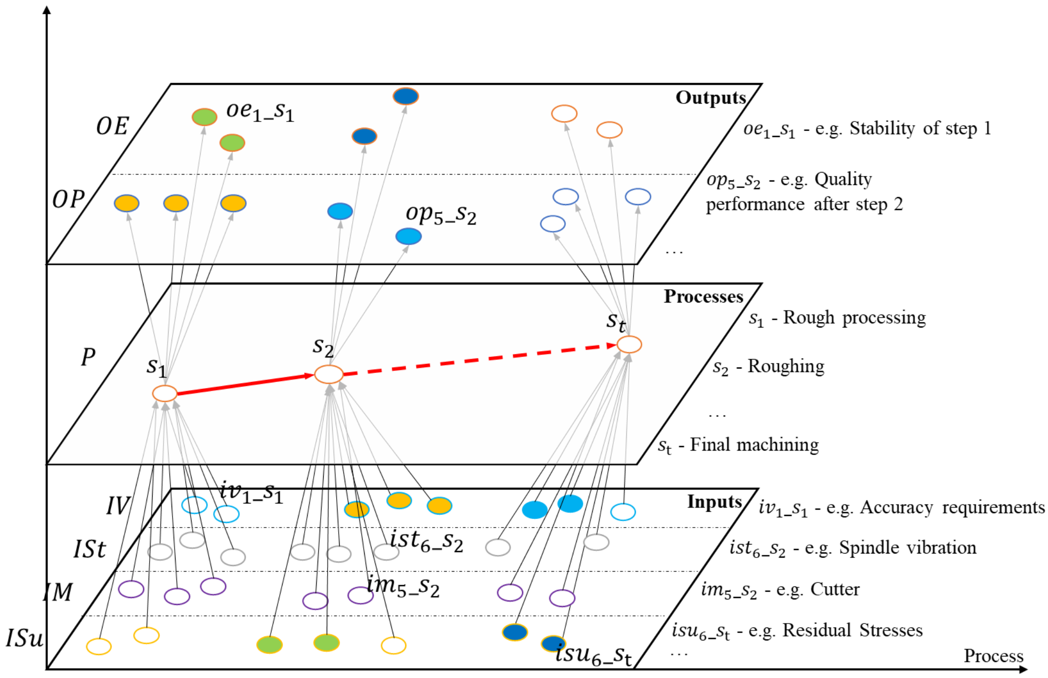


FIGURE 4. Digital description of IPO elements in eDMAIC.

shown in Eq. (1).

$$C = (IV, ISt, IM, ISu, P, OP, OE) \quad (1)$$

where

C	- set of all the elements in this eDMAIC project,
$IV = \{iv_1, iv_2, \cdots, iv_a\}$	- set of VOC Elements in Input, and $iv_1\_s_1$ means the first VOC input for first machining process,
$ISt = \{ist_1, ist_2, \cdots, ist_b\}$	- set of State Elements,
$IM = \{im_1, im_2, \cdots, im_c\}$	- set of Machining Elements,
$ISu = \{isu_1, isu_2, \cdots, isu_d\}$	- set of Supply Elements,
$P = \{s_1, s_2, \cdots, s_t\}$	- set of Processes while machining,
$OP = \{op_1, op_2, \cdots, op_p\}$	- set of Product Elements,
$OE = \{oe_1, oe_2, \cdots, oe_q\}$	- set of Evaluation,

All these elements should be measurable or quantifiable, and some subjective indicators should be converted by brainstorm or other scientific methods/tools. The inputs of the subsequent process are the outputs of the pre-process, which shown as the same colour in Figure 4.

C. ANALYSE

After the **measure** phase, a *Machining Error Prorogation Network*(MEPN) needs to be constructed and a key process should be figured out. Then, an accurate analysis approach based on a precise sensing network around this key process needs to be set up, along with a reliable and lower-delay machining data collecting system.

1) MODEL THE MACHINING PROCESS WITH COMPLEX NETWORK THEORY

The general MEPN can be modelled as

$$G_k = \langle V_k, E_k \rangle \quad (2)$$

where the nodes set

$$\begin{aligned} V_k &= \{IV_k, ISt_k, IM_k, ISu_k\} \cup \{OE_k, OP_k\} \\ &= IV_k \cup ISt_k \cup IM_k \cup ISu_k \cup OE_k \cup OP_k \end{aligned} \quad (3)$$

and the edges set E_v is the relationship link between related v_k.

$$E_v = \{e_{12}, e_{13}, \cdots, e_{mn}\} \quad (4)$$

The directions of edges are with machining logic, and $s_1 \rightarrow s_2 \rightarrow \cdots \rightarrow s_t$ indicates the machining flow. e_{mn} implies the weight of edge from v_m to v_n. The basic weight of each edge defines as 1, and it grows with the links increase.

And the global EPN can be described as

$$\begin{aligned} G &= \langle V, E \rangle = G_1 \cup G_2 \cup \cdots \cup G_t \\ &= \langle V_1, E_v \rangle \cup \langle V_2, E_v \rangle \cup \cdots \cup \langle V_t, E_v \rangle \\ &= \langle V_1 \cup V_2 \cup \cdots \cup V_t, E_v \rangle \\ &= \langle \{V_1 \cup V_2 \cup \cdots \cup V_t\}, \{e_{12}, e_{13}, \cdots, e_{mn}\} \rangle \end{aligned} \quad (5)$$

2) FIGURE OUT THE KEY PROCESS

After modelling the MEPN, metric analyses for EPN should be done [42]. Figure 5 shows the logic flow of the metrics analysis method.

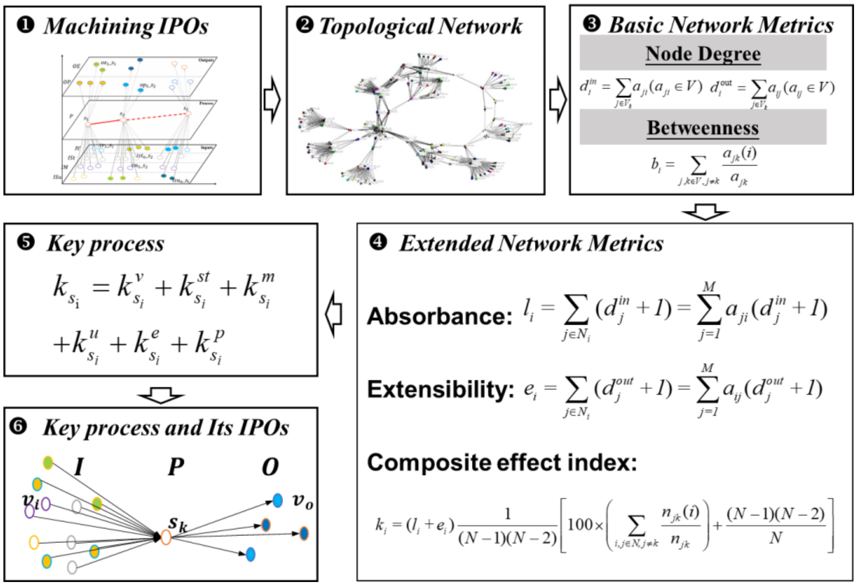


FIGURE 5. The logic flow of the metrics analysis method.

TABLE 2. The calculation method for metrics in MEPN.

Metric	Symbol	Definition	Calculation formula
Degree	d_i	The importance of node i to some extent, which has two components: in-degree d_i^{in} and out-degree d_i^{out}.	$d_i^{in} = \sum_{j \in V_k} a_{ji}(a_{ji} \in V)$, $d_i^{out} = \sum_{j \in V_k} a_{ij}(a_{ij} \in V)$, $d_i = d_i^{in} + d_i^{out}$
Betweenness	b_i	The connectedness of i.	$b_i = \sum_{j,k \in V, j \neq k} \frac{a_{jk}(i)}{a_{jk}}$
Absorbance	l_i	Neighbour nodes influence node i.	$l_i = \sum_{j \in N_i} (k_j^{in} + 1) = \sum_{j=1}^{M} a_{ji}(k_j^{in} + 1)$
Extensibility	e_i	Node i influences neighbour nodes.	$e_i = \sum_{j \in N_i} (d_j^{out} + 1) = \sum_{j=1}^{M} a_{ij}(d_j^{out} + 1)$

Node Degree was defined to help to figure out the key node (process) in the machining process, which indicates the importance of node i to some extent. The degree of node i has two components, in-degree d_i^{in} and out-degree d_i^{out}. And the ***Betweenness*** metric was defined to measure the importance of node i in the whole network. Calculating methods for these two basic metrics can be seen below (in Table 2).

To better understand the relationships between network structures, it is necessary to identify the importance in MEPN by *Composite Effect Index*, detail in equation

$$k_i = (l_i + e_i)\frac{1}{(N-1)(N-2)} \times \left[100 \times \left(\sum_{i,j \in N, j \neq k} \frac{n_{jk}(i)}{n_{jk}}\right) + \frac{(N-1)(N-2)}{N}\right] \quad (6)$$

then the importance value of the process k_{s_i} can be calculated with

$$k_{s_i} = k_{s_i}^v + k_{s_i}^{st} + k_{s_i}^m + k_{s_i}^u + k_{s_i}^e + k_{s_i}^p \quad (7)$$

Then ranking k_{s_i}, the key machining process will be selected. The performance of this node will affect the total performance a lot in the M/S/O machining process.

3) CPS-DRIVEN MACHINING DATA SENSING

Key machining process will be used for the following improving stages, in which the accurate calculation needs to a reliable machining data collecting system with lower delay. Cyber-Physical Systems (CPS) is defined as transformative technologies for managing interconnected systems between its physical assets and computational capabilities [43]. So, a CPS-driven monitoring system for controlling the key process quality of machining, together with its machining conditions real-timely is necessary. Assuming k^{th} process is the key process, and extract the whole relevant IPOs of process k, which shown as the 6$^{\text{th}}$ phase in Figure 5.

D. IMPROVE

After analysing the key machining process and its corresponding IPOs, a sensitivity tool and a stability index are introduced to evaluate and improve the key machining process.

1) MODELLING AND CALCULATING THE INPUTS SENSITIVITY OF KEY MACHINING PROCESS

The relationships between inputs and outputs are multivariate and nonlinear, which is difficult to construct a conventional mathematical model to express the mapping relation. Then the multivariate nonlinear relation can be expressed with

$$v_o^i = f\left(v_i^1, v_i^2, \cdots, v_i^l\right) (l \in k_{s_i}^e, k_{s_i}^p) \tag{8}$$

where v_o^i is the error performance of output i, and $f(\cdot)$ is the mapping between input factors and outputs. v_i^1 stands for measuring value by CPS and each v_o^i can be influenced by all the factors.

Different error factors have different influence levels on the formation of the outputs feature, and the influence value is defined as the *Error Fluctuation Sensitivity* (EFS) of the output feature to the input factor. Higher EFS value means this factor is more sensitive to the performance. So, the purpose of EFS analysis is deciding the most sensitive factors that may be controlled in the *Control* phase a lot.

The calculation of EFS can be shown as

$$S_k^i = \left|\frac{\partial f(x_i)}{\partial x_i}\right| = |\nabla x_i f(x_i)| \tag{9}$$

where S_k^i is the EFS of the quality feature k to the error factor x_i, x_i is the deviation of the vector $\mathbf{x}$, $f(\cdot)$ is the mapping relation between error factors and the quality feature k, $\nabla x_i f(\mathbf{x})$ is the gradient of $f(\cdot)$ at the error factor x_i. Then the whole quality performances to all the sensitivities of input factors can be expressed as

$$\mathbf{J} = \begin{pmatrix} \frac{\partial f(x_1)}{\partial x_1} & \cdots & \frac{\partial f(x_1)}{\partial x_i} & \cdots & \frac{\partial f(x_1)}{\partial x_n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \frac{\partial f(x_k)}{\partial x_1} & \cdots & \frac{\partial f(x_k)}{\partial x_i} & \cdots & \frac{\partial f(x_k)}{\partial x_n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \frac{\partial f(x_m)}{\partial x_1} & \cdots & \frac{\partial f(x_m)}{\partial x_i} & \cdots & \frac{\partial f(x_m)}{\partial x_n} \end{pmatrix} \tag{10}$$

where $\mathbf{J}$ is the Jacobian matrix of EFS and after the normalization of the sensing data, the $\mathbf{J}$ can be calculated.

2) EVALUATE THE STABILITY INDEX

Based on performance distribution analysis approach [43], sensitivity analysis tool can be used as follows. The error outputs variation caused by the input errors can approximately represent the linear expansion of Eq. (11) because of the attribute of the Jacobian matrix.

$$\mathbf{y} = \mathbf{J}\mathbf{x} \tag{11}$$

where $\mathbf{y} = (f(x_1), f(x_2), \cdots, f(x_m))^T$ is the input vector, $\mathbf{J}$ is the sensitivity Jacobian evaluated at the nominal value of the input. $\mathbf{x} = (x_1, x_2, \cdots, x_n)^T$ is input errors vector. Assuming the n input errors of $\mathbf{x}$ are independent, and the space expanded by these components of $\mathbf{x}$ is n dimensionality. The n-dimensional space can be called the variation space $S_v\{\mathbf{x}\}$.

The relationship between the outputs and the inputs can be established by taking a norm of the vector

$$\begin{aligned} \|\mathbf{y}\|_2^2 &= f(x_1)^2 + f(x_2)^2 + \cdots + f(x_m)^2 \\ &= \mathbf{y}^T\mathbf{y} = \mathbf{x}^T\mathbf{J}^T\mathbf{J}\mathbf{x} \end{aligned} \tag{12}$$

where the $\|\mathbf{y}\|_2^2$ denotes Frobenius norm. Let $\mathbf{A} = \mathbf{J}^T\mathbf{J}$ represent the error propagation characteristic matrix. The n-dimensional symmetric matrix $\mathbf{A}$ defines a quadratic

$$\|\mathbf{y}\|_2^2 = \mathbf{x}^T\mathbf{A}\mathbf{x} \tag{13}$$

Since the definition of the vector norm implies $\|\mathbf{y}\|_2^2 \geq 0$, the matrix $\mathbf{A}$ of the quadratic must be either positive or semi-positive (nonnegative) definite.

The matrix $\mathbf{A}$ must have n orthonormal eigenvectors and n nonnegative eigenvalues λ_i $(i = 1, 2, \cdots, n)$ among which the number of positive eigenvalues is equal to the rank of $\mathbf{A}$ according to the matrix theory. So, sort these eigenvalues by value, i.e. $0 \leq \lambda_1 \leq \lambda_2 \leq \cdots \leq \lambda_n$, and denote the corresponding orthonormal eigenvectors as $\boldsymbol{\upsilon}_i$ $(\upsilon = 1, 2, \cdots, n)$. Then the *Safety Feasible Space* (S_{sf}) and *the Real Feasible Space* (S_{rf}) can be calculated separately.

S_{sf} is the virtual safety space in higher dimensions while machining, and the machining sensitivity distribution can be geometrically represented with an n-dimensional variable space. Here are two cases, Figure 6 shows the calculation procedures and the sensitivity distribution in geometric form. It is believed that the instantaneous machining condition will be stable when the comprehensive sensitivity is inside S_{sf} in geometric relations.

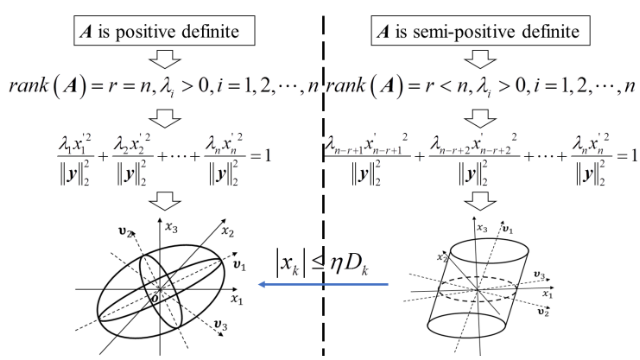


FIGURE 6. Two kinds of S_{sf} in geometric space.

In the second case, no matter how strong the variations of the inputs are, the outputs will not be affected at all. It seems unreasonable from a factual point of view. So, a revised indicator η is needed.

S_{rf} are the tolerances of the input errors or disturbances, which can be expressed with

$$S_{rf} = \{x|t_{li} \leq x_i \leq t_{ui},\ i = 1, 2, \cdots, n\} \tag{14}$$

where

t_{li} - the i^{th} lower deviation of input error or the best condition of the disturbance;

t_{ui} - the i^{th} upper deviation of input error or the limiting condition of the disturbance.

As S_{rf} delimits the varietal range of x_i, all the input errors are expected to be within this space. Hence, the S_{rf} must be an n-dimensional block space enclosed by the $2n$ planes. The i^{th} side lengths of the block are equal to $t_{ui} + t_{li}$. The relationship between S_{rf} and S_{sf} is illustrated in Figure 7 (when $n = 2$).

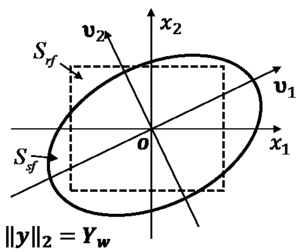


FIGURE 7. Safety Feasible Space and Real Feasible Space when $n = 2$ in geometric space.

Then the stability index S_{pok} was employed to evaluate the machining process. And its value can be calculated by comparing the positional relation and volume relation between S_{rf} and S_{sf}. The specific calculation process can be seen in the literature [44] and this article will not repeat them. According to the recommended minimum process stability, some controlling approaches must be done as Figure 8 shows.

E. CONTROL

As Figure 8 shows, the value of EFS should be calculated to figure out the most and the least sensitive factors. The relation between quality performances and the inputs factors can be figured out by solving the nonlinear multiple equations. There are several methods which can deal with the evaluating problems. This paper offers an available approach - *Support Vector Regression Machine* (SVRM) [45] - as an example to solve this nonlinear fitting with global optimization. It is pointed that the best fitting function can be expressed

$$\begin{aligned} f(\mathbf{x}) &= \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^*\right) K(\mathbf{x}, \mathbf{x}_i) + b \\ &= \sum_{\mathrm{i}=1}^{\mathrm{N}} (\alpha_{\mathrm{i}} - \alpha_{\mathrm{i}}^*) \exp\left\{-\frac{\|\mathbf{x} - x_i\|^2}{2\delta^2}\right\} + \mathbf{b} \end{aligned} \tag{15}$$

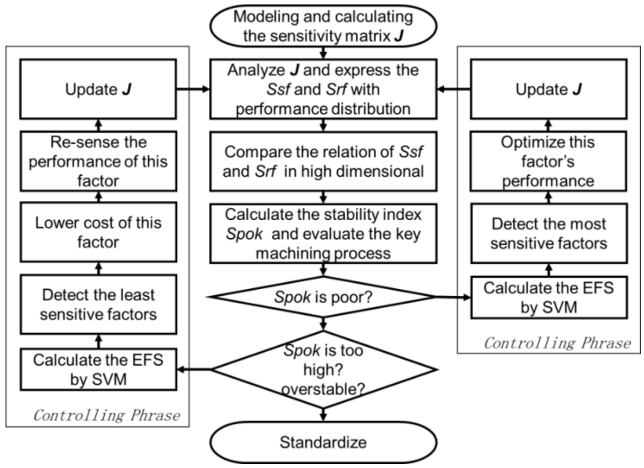


FIGURE 8. Evaluating flow and the connections to the *Control* phrase.

where $K(\mathbf{x}_i, \mathbf{x}) = \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}\|}{2\delta^2}\right)$ is the kernel function. The EFS can be calculated with the derivative of Eq. (15), which shows in Eq. (16).

$$S_k = \sum_{\mathrm{i}=1}^{\mathrm{N}} (\alpha_{\mathrm{i}} - \alpha_{\mathrm{i}}^*) \frac{(x_i - x)}{\delta^2} \exp\left(-\frac{\|x_i - x\|^2}{2\delta^2}\right) \tag{16}$$

Define the included angle of $\frac{\partial f(x_k)}{\partial x_i}$ and e, where $e = (e_1, e_2, \cdots, e_i, \cdots, e_n)$, $e_i = 1$ are the unit vectors. And the EFS can be expressed with

$$\eta_k = \begin{cases} \arccos\left(\dfrac{S_k e}{\|S_k\|\,\|e\|}\right) & S_k e \geq 0 \\ \pi - \arccos\left(\dfrac{S_k e}{\|S_k\|\,\|e\|}\right) & S_k e < 0 \end{cases} \tag{17}$$

1) CONTROL THE PROCESS QUALITY

The goal of controlling the process quality is about to adjust some key parameters to achieve better performance with lower cost. Obviously, the most important input factor will have the highest EFS value. The lower values of these factors are, the more helpful to reduce the output errors. So, some improvements, such as creating better machining condition, getting a better monitoring or even some adjusting of processes' orders should be done. It is pointed that whatever controlling approach it chose, only one parameter will be adjusted at a time. Provided that several adjustments were done at the same time, the process might become more unstable.

2) CONTROL THE MACHINING SYSTEM

As the final sub-phase of the whole eDMAIC project, controlling the machining system plays a vital role in improving the whole manufacturing system with the processes, procedures and operating instructions' modifying. In the meantime, good experiences, operations, formed flow, and even data should be standardized for more effective management.

V. CASE STUDY

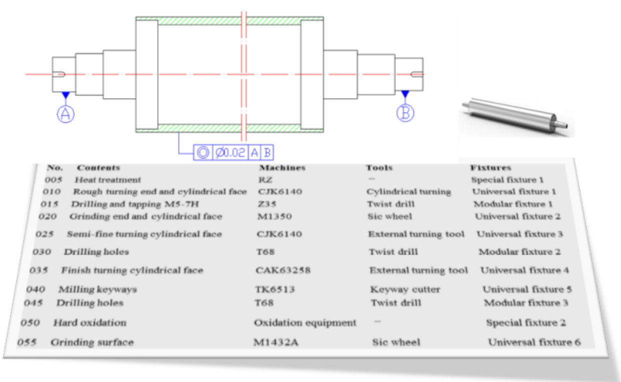
To illustrate how the proposed eDMAIC method works, a specific case will be discussed below. This case was from one of machining workshop in *Shaanxi Beiren Printing Machinery Co., Ltd.*, which committed to the high-end printing manufacturing. This section will focus on its machining process with eDMAIC method, which forms the project's determining to the final application effect. Corresponding to the five phases in section 4, the case will be discussed from the following aspects.

A. DEFINE

This phase contains the factors of the object, goals, team, and timeline of the eDMAIC project, some indicators are as follows:

a) Object - Guide Roller WIPs machining process
b) VOC Goals - Concentricity meets design requirements
c) Strategic Objectives Goals - Better concentricity performances
d) Operations Goals - That is the coaxiality error of guiding rolls ranges from φ0.04mm to the expected φ0.02mm

Printing equipment manufacturing, as a kind of small-batch manufacturing, which workshop is a typical MW and its key parts - the Guide Roller WIPs are meeting the requirements of the checklist in Figure 2. Taking a batch 2017 $***$ 304 as an example, which contains 12 WIPs and each of them has 11 main machining processes, which shows in Figure 9.



No.	Contents	Machines	Tools	Fixtures
005	Heat treatment	RZ	—	Special fixture 1
010	Rough turning end and cylindrical face	CJK6140	Cylindrical turning	Universal fixture 1
015	Drilling and tapping M5-7H	Z35	Twist drill	Modular fixture 1
020	Grinding end and cylindrical face	M1350	Sic wheel	Universal fixture 2
025	Semi-fine turning cylindrical face	CJK6140	External turning tool	Universal fixture 3
030	Drilling holes	T68	Twist drill	Modular fixture 2
035	Finish turning cylindrical face	CAK63258	External turning tool	Universal fixture 4
040	Milling keyways	TK6513	Keyway cutter	Universal fixture 5
045	Drilling holes	T68	Twist drill	Modular fixture 3
050	Hard oxidation	Oxidation equipment	—	Special fixture 2
055	Grinding surface	M1432A	Sic wheel	Universal fixture 6

FIGURE 9. Guide rollers WIPs.

Then, a Guide Roller machining process was picked up as an eDMAIC project. The WIPs was produced for the assembly workshop, whose requirements are the VOC goal. That the operations' goal is reducing the coaxiality error to φ0.02mm after machining, which detail shows in Figure 9.

B. MEASURE & ANALYSE

The Measure phase contains two steps - analyse the IPOs of each process and digitalized them. Part of the result can be seen in Table 3.

The matrix of the relation between different factors are figured out. Then the MEPN of the Guide Roll can be built

TABLE 3. IPOs for the guide roller in eDMAIC project.

	P	*IV*	*ISt*	*IM*	*ISu*	*OP*	*OE*
005	s_1	$iv_1\_s_1$ - Executing as Manual $iv_2\_s_1$ - Higher Hardness	$ist_1\_s_1$ -Formula Deviation. $ist_2\_s_1$ -Time Deviation. $ist_3\_s_1$ -Temperature Deviation.	…	…	…	…
010	s_2	…	…	…	…	…	…
…	…	…	…	…	…	…	…
055	s_{11}	…	…	…	…	…	…

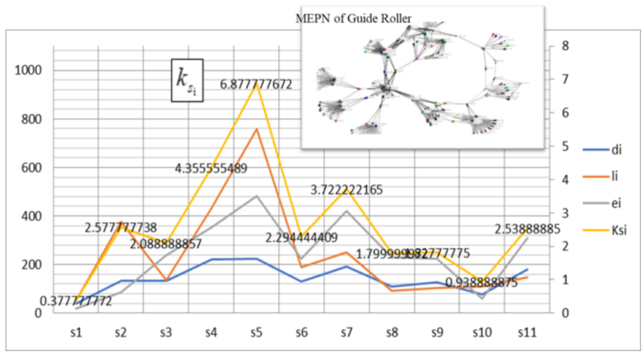


FIGURE 10. MEPN Values of d_i, l_i, e_i and k_{s_i} in each process.

and the value of k_{s_i} will be shown in Figure 10 according to Eq. (7). When $i = 5$, whether the k_{s_i} is the highest, which means the process NO. 025 (Process 5) is the key process.

The matrix of the relation between different factors showed in Appendix 2 and Appendix 3. Then the MEPN of the Guide Roll can be built and the value of k_{s_i} will be shown in Figure 10 according to Eq. (7). When $i = 5$, whether the k_{s_i} is the highest, which means the process NO. 025 (Process 5) is the key process.

As Table 3 shows, the key Process 5 has 12 kinds of inputs and 7 kinds of outputs. The CPS-driven machining data sensing network will be used for collecting original data and these data must be normalized as Appendix 4 shown. There are 18 groups, which mean 18 independent parts' machining processes.

C. IMPROVE & CONTROL

Then calculating the EFS with FSVM in the Improve phase, and the result can be seen in Figure 11. Higher value means the higher the important factors, which values must be under control for the better performance of outputs. In this case, the $iv_1\_s_5$, $ist_2\_s_5$, $ist_3\_s_5$, $im_3\_s_5$, $isu_1\_s_5$, $isu_4\_s_5$ are the key factors.

Taking the Process 5 in 18 WIPs as an evaluating goal, establish the S_{sf} and the S_{rf}, which are in a 7-dimensional space. Calculate the stability index S_{pok} with the defined algorithm, S_{pok} equals to 1.40, which means unstable,

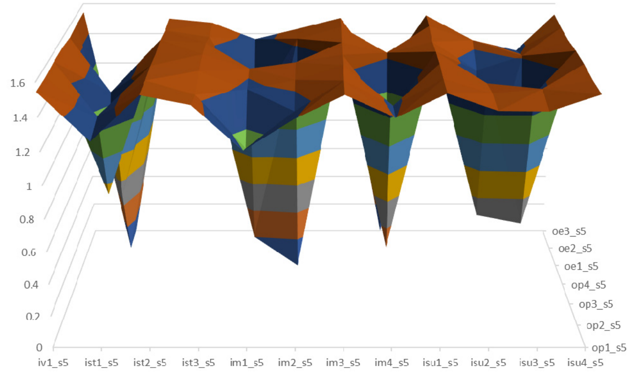


FIGURE 11. The EFS of process 5.

the machining condition and the machining process should be improved.

The final phase is controlling the key factors selected by FES analysis in Evaluate phase. How to control the value of these factors can be seen in Table 4 detailly.

TABLE 4. Factors controlling.

	Error Factors	Improvement Controlling
$Iv_1\_S_5$	M.E.	Do as Manual Strictly
$Ist_2\_S_5$	Tool V.	Monitor and Control the Vibration of Tool
$Ist_3\_S_5$	Temperature D.	Monitor and Control the Temperature in Best Situation
$Im_3\_S_5$	Universal Fixture 3	Better Performance in Fixture 3
$Isu_1\_S_5$	D.E. Of Length	Control the Dimensional Error in Process 4
$Isu_4\_S_5$	S.R.	Control the Surface in Process 4

In the machining system controlling level, the whole eDMAIC process can be summarized as *Standard Operating Procedure* (SOP). In this case, SOP will be written into the processing handbook.

VI. DISCUSSION AND CONCLUSIONS

This proposed eDMAIC method, as a modification and extension of the popular Six Sigma, is a novel approach for quality controlling and continuous process improving in MW, which offers a systematic solution where the machining processes are usually unstable because of the limiting factors in M/S/O. eDMAIC method is based on the traditional DMAIC, and it designed for the better-quality performance of M/S/O WIPs with low cost drawing on Six Sigma's thinking. It can fill the gaps in the standardization of machining processes' controlling in M/S/O production, which drives the Six Sigma Management be suitable for more scenes.

It is known that the DMAIC improvement cycle is the core tool used to drive Six Sigma projects refers to data-driven improving, optimizing and stabilizing processes. During its five stages of DMAIC, a team always chooses the managerial and statistical tools which deems most suitable, and the DMAIC projects have also achieved lots of quality and economic benefits in a variety of applications. But in the process of non-mass manufacturing, it seems difficult to find the proper tools to overcome the lack of enough data and samples. The proposed eDMAIC method offers a way of data-driven application for the M/S/O production and provides unique tools in every phase. It is proved that eDMAIC is feasible and effective in this situation.

This paper is intended to be a guide for the quality practitioner, who works via a continuous improvement tool when the statistical tool cannot be used. And the improvement ideas also come from team members. The only difference here is that data are collected and analysed along the machining to validate the assumptions. Different goals in different phases are clear and their operational processes are also described unequivocally. In the end, an industrial case is provided to assist to understand the subject matter.

eDMAIC method is more like a universal framework, which contains several of specific tools in each phase. Specific tools can be integrated into it and there are some tools listing, which can deal with the small samples in continuous machining. It is believed that this method can support the conclusions or decisions and not necessarily undertake a full-fledged continuous improvement project.

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